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China's 19-year city-level carbon emissions of energy consumptions, driving forces and regionalized mitigation guidelines

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ABSTRACT

Due to the lack of city-level energy consumption statistics and the inconsistency between national, provincial and city-level data, we developed a normalized approach for assessing China's city-level CO_2 emissions of energy consumptions using DMSP/OLS nighttime light imageries and explored major driving forces for proposing feasible mitigation policies. China's CO_2 emission process was always consistent with its economic development and was classified into two rapid periods (1999–2002 and 2007–2010) and two slow periods (1992–1999 and 2002–2007). Most cities in Western, Central and Northern China belonged to the slow growth type, while most cities in Eastern China belonged to the rapid growth type. Cities with huge CO_2 emissions mainly congregated in southern and eastern coastal areas. Contrarily, cities with small amount of CO_2 emissions were mainly located in southwestern inlands. The CO_2 emission per capita (PCCE) in Northeastern and Eastern China was higher than that of Western and Central China. While the CO_2 emission per GDP (PGCE) of Northeastern and Western China was higher than that of Eastern and Central China. GDP increment was the major factor determining the carbon-emission growth rate, while industry structures and energy efficiencies were the major factors influencing regional CO_2 emission intensities. Therefore, in order to decrease the growth rate of China's CO_2 emissions but not hinder its economic development, major efforts should be focused on optimizing the industrial structures in Eastern and Central China where industries mainly belonged to technology-intensive, labor-intensive and light industry types, and guiding companies to increase the energy efficiencies in Northeastern and Western China, where industries mainly belonged to heavy and energy-related types. In particular, more attention should be paid to prevent the CO_2 emissions per energy consumption (PECE) of underdeveloped cities or provinces from increasing rapidly rather than only focusing on reducing the PECE of developed regions.

Contents

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1. Introduction

During the past three decades, significant climatic changes had been observed globally, of which global warming was the most obvious [1]. Carbon dioxide (CO_2) emission, which was responsible for more than 60% of greenhouse effects, was proved to be the leading contributing factor [2]. Due to global economic development, continuously increasing amounts of energy consumptions directly induced the high-rise of CO_2 emissions over the past century [1]. Thus, it was urgent for academics and practitioners to intensively assess the CO_2 emissions of energy consumptions all over the world, especially in the rapid developing countries [3].

China, which has been experiencing a remarkable growth of gross domestic product (GDP) with average annual rate of 9.8% since the "Reform and Opening Up" in 1978 and ranked the third in the world in 2009, attracted global attentions [4]. Rapid economic growth and industrialization inevitably led to a large amount of substantial energy consumptions and thereby increased China's CO_2 emissions significantly. According to the United Nations Statistics of 2010, China has surpassed the United States and became the largest CO_2 emitter, sharing 24.2% of the world's total amount [5]. Maintaining the current rate of industrialization and urbanization process, China would probably produce even-larger CO_2 emissions in the future, which also attracted great international concerns [1,6]. In 2008, the Kyoto Protocol severely pointed out the responsibilities of developing countries to participate in reducing the CO_2 emissions internationally [7]. The Chinese government promised to reduce 40–45% of CO_2 emission intensities by 2020 compared to the 2005 level in the COP15 United Nations Climate Change Conference. A dilemma between the developments of national economy and reductions of CO_2 emissions, therefore, has been popped up for the Chinese government. This again raised global concerns but there were still no practical carbon curb solutions [5]. In other words, reducing China's CO_2 emissions was not only an urgent and important mission for China, but also the hottest international concern of the whole world [8]. Hence, to solve this dilemma, the first step was to investigate the spatial and temporal characteristics of China's CO_2 emissions, potential driving forces and to make robust carbon reduction polices.

Many researches have been conducted to assess the CO_2 emissions of energy consumptions and economic activities in China [6,7,9–15]. However, most of them depended on the statistical data published by China's national, provincial and municipal Bureau of Statistics. As the statistical approach on data collection, reporting and validation was opaque, there were always significant discrepancies between national, provincial and city-level official statistics of energy consumptions [16–19], which thereby led to unreliable conclusions. Additionally, few former studies have focused on the city-level CO_2 emissions because the city-level statistics of energy consumptions were always blank in some special decades, especially in underdeveloped regions. As city was the basic administrative unit to implement the carbon reductions in China [20–22], it was important to develop a reliable city-level CO_2 emission inventory for making viable CO_2 mitigation polices [23,24].

Studies have proved that it was feasible to monitor the periodic socio-economic activities such as human population, GDP, and electrical power consumption by using the Operational Line-scan System (OLS) night-time light (NTL) data from the Defense Meteorological Satellite Program (DMSP) [25–27]. It was found that anthropogenic CO_2 emissions were directly correlated with population, GDP and electrical power consumption. Theoretically, it was viable to estimate regional CO_2 emissions from DMSP/OLS NTL data. This approach has been proved by some researches, which successfully estimated the global and continental gross CO_2 emissions based on DMSP/OLS NTL imageries [28,29]. However, these studies still focused on the CO_2 emissions of global, continental and national levels but not the city-level. In particular, they mainly aimed to develop an effective model for estimating the total amounts of CO_2 emissions but failed to explore the driving forces and to propose corresponding mitigation policies.

To fill up the gaps of historical city-level CO_2 emissions and unify the national, provincial and city-level statistical data of China, this paper aimed at the following objectives: (1) to develop a normalized faithful approach for assessing China's city-level CO_2 emissions of energy consumptions from 1992 to 2010 using DMSP/OLS NTL imageries; (2) to analyze the spatial and temporal dynamics of China's 19-year CO_2 emissions; and (3) to reveal the major driving forces in different regions and propose corresponding potential mitigation policies.

2. Study areas and materials

2.1. Study areas

Mainland China, with population of 1.34 billion and GDP of 6.04 trillion US$ at the end of 2010, has about 300 prefecture cities. Since the economic reform in 1978, a rapid process of economic development and urbanization has taken place throughout China, especially in coastal areas. It directly led to great economic

imbalances between different cities and finally formed 4 economic regions. According to geographical position and economic development level, Mainland China was divided into Eastern China, Central China, Western China and Northeastern China (Fig. 1). Spatial and temporal characteristics of CO_2 emissions of the 4 economic regions were analyzed and compared in order to reveal the major driving forces.

2.2. Materials

Time-series DMSP/OLS NSL datasets for years 1992–2010 were obtained from the National Geophysical Data Center (NGDC). The sensors mainly captured stable lights emitted from cities, towns, country-sides and other sites with persistent lighting. The NSL imageries were developed after removing the light noise caused by fire and other incidental background noises and presented the global annual average brightness in units of 6-bit digital numbers (DN) ranging from 0 to 63, with spatial resolution of 30″ [25,28,30]. The time-series DMSP/OLS NTL data were obtained by different sensors on different satellites. Therefore, they could not be directly used for estimating the CO_2 emissions because of lack of comparability [25,31,32]. In order to reduce the discrepancies, Elvidge's approach [25] was used to correct the time-series DMSP/OLS NTL data of China.

The primary energy consumption statistics of 31 provinces and certain cities (Beijing, Shanghai, Guangzhou, and Shenzhen) from 1992 to 2010 were extracted from the Statistical Yearbook for calculating statistical CO_2 emissions. Corresponding GDP and population data were also extracted from the Statistical Yearbook for calculating the CO_2 emission intensities.

3. Methods

3.1. Formulas for calculating the statistical carbon emissions and carbon emission intensities per GDP and per capita

The Intergovernmental Panel on Climate Change (IPCC) provided fundamental guidelines and unified standards of assessment of the CO_2 emissions from greenhouse gases internationally. The IPCC method was used to calculate the statistical CO_2 emissions of energy consumptions in Mainland China. The conversion formula is

$$CO_2 = \frac{44}{12}\sum_{i=1}^{9} K_i E_i \quad (1)$$

where i represents the types of energy, such as raw coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas, heat and electricity. E_i represents the stand coal consumption of energy type i. According to the IPCC guidelines, various types of fuel consumptions could be converted to a standard coal consumption based on the calorific value of each fuel type. K_i represents the effective CO_2 emission factor of each energy type: 44/12 represents the molar ratio of CO_2 to C. The conversion factor of power generation coal to standard coal consumption (SCE) and CO_2 emission factor for different energy types are listed in Table 1.

Using the total CO_2 emission data and corresponding statistical GDP and human population data, the CO_2 emissions per GDP (PGCE) and per capita (PCCE) for each administrative unit from 1992 to 2010 were calculated using the following formulas:

$$PGCE = CO_2/GDP \quad (2)$$

$$PCCE = CO_2/P \quad (3)$$

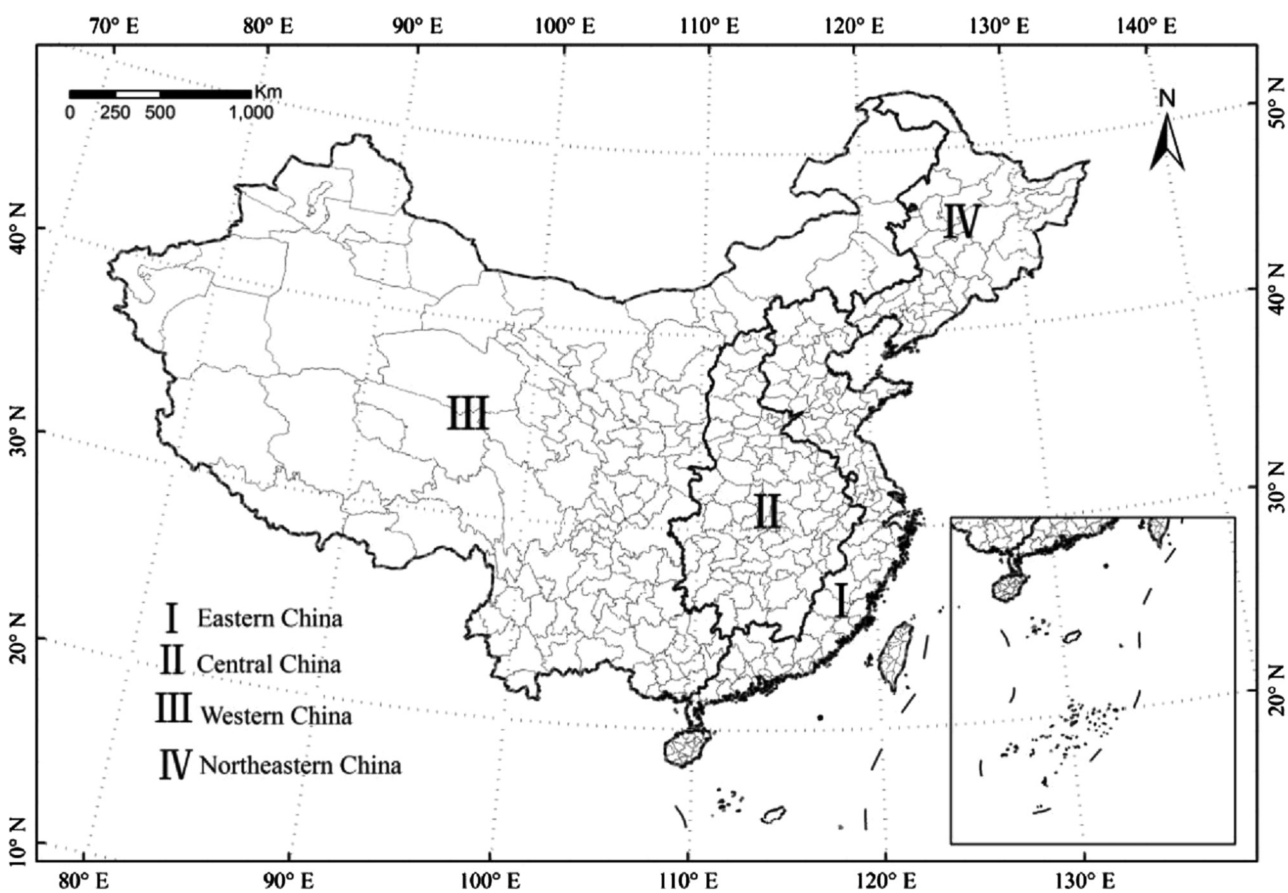

Fig. 1. Study area.

Table 1
Conversion factor of power generation coal to standard coal consumption and CO_2 emission factor for different types of energy.

Energy type	Raw coal	Coke	Crude oil	Gasoline	Kerosene	Diesel oil	Fuel oil	Natural gas	Heat	Electricity
SCE conversion factor (tSCE/t)	0.7143	0.9714	1.4286	1.4714	1.4714	1.4571	1.4286	1.33	34.12[a]	–
CO_2 emission factor (10^4 tC/10^4 tSCE)	0.7559	0.855	0.5857	0.5538	0.5714	0.5921	0.6185	0.4483	0.67	0.272[a]

[a] The unit of heat conversion to SCE is tSCE/10^9 kJ; the unit of electricity conversion to CO_2 emission is 10^4 t C/10^7 kWh.

where *GDP* represents the total gross domestic product and *p* represents the total human population.

3.2. Relationship between DMSP/OLS night lights and statistical carbon emissions

A unique urban-area mapping method was developed to semi-automatically distinguish China's urban regions from the non-urban background [26,33–35] (Appendix A). Based on the extracted construction lands, the total DMSP/OLS DN values for each province and city were separately counted. Correlation coefficient between statistical CO_2 emissions and the total DMSP/OLS DN values of the same province or city was also calculated (Fig. 2). Results indicated that there was a significant linear relationship between DMSP/OLS night lights and statistical CO_2 emissions ($R=0.91$, $p<0.001$). The fitted formula was as follows:

$$CO_2 = \mathrm{SDN}/0.041 \quad (4)$$

where SDN represents the total DMSP/OLS DN values.

In total, 314 samples of provincial and city-level statistical CO_2 emissions were used to validate the simulated CO_2 emissions (Fig. 3). The root mean square error (RMSE) between simulated CO_2 emissions and statistical CO_2 emissions at provincial and city-level was approximately 943.79×10^4 t, with relative error of 7.65%. Based on this approach, the national-level RMSE between simulated CO_2 emissions and statistical CO_2 emissions equaled to 4.66×10^8 t, with average relative error of 5.15%. Results indicated it was a feasible and reliable method to reconcile China's city-level CO_2 emissions with its national-levels using DMSP/OLS remote sensing technologies.

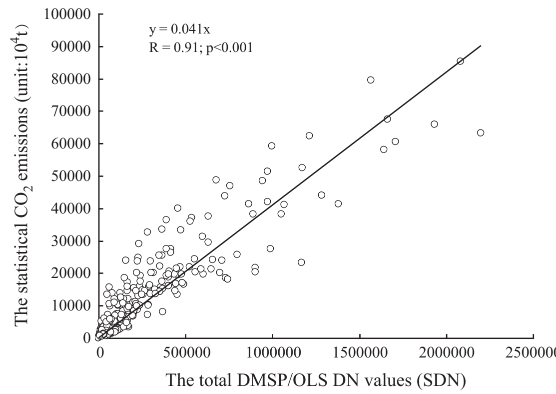

Fig. 2. Correlation analysis between the total DMSP/OLS night light values and CO_2 emissions calculated from statistical energy consumption data.

3.3. Moran's I and SLOPE indices for analyzing the spatial and temporal variations of carbon emissions

Global and local Moran's *I* indices were used to evaluate the spatial patterns of city-level CO_2 emissions in Mainland China [36]. The global Moran's *I* index mainly reflected the nationwide spatial correlation between different geographical regions, while the local Moran's *I* index mainly reflected the local similarities and variations between neighboring cities. The ranges of both global and local Moran's *I* indices were from -1 to 1. The positive values indicated the degrees of similarities while negative values indicated the degrees of differences.

Two variables (*z*-score and *p*-value) were calculated for each city to clarify the spatial correlation types. *z*-Score and *p*-value indicated the spatial correlation level and corresponding significant level between the neighbored cities respectively. If *z*-score of the two neighbored cities was higher than 1.96 (p-value <0.05), then these two cities will be classified as the significant similarity type (High–High cluster or Low–Low cluster type). Contrarily, if *z*-score of the neighbored cities was smaller than -1.96 (p-value <0.05), then the two cities will be classified as the significant variation type (High–Low cluster or Low–High cluster type).

Further, another two variables (the global mean and the local mean) were calculated to clarify the spatial cluster types. The global mean was the average *z*-score of all cities; while the local mean was the average *z*-score of the target city's neighbors. The cities with *z*-scores that were higher than the local mean were classified as High–Low cluster, and those cities with values lower than the local mean were classified as Low–High cluster. The cities with local means that were higher than the global mean were classified as High–High cluster type, and those with local means lower than the global mean were classified as Low–Low cluster type.

According to He et al. [37], a linear regression model named SLOPE index (formula (5)) was proved to be effective in describing the changing trends of time-series data. The SLOPE index method was used in this paper to describe the variation trends of China's 19-year city-level CO_2 emissions from 1992 to 2010.

$$\mathrm{SLOPE} = \frac{n\sum_{i=1}^{n} x_i C_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} C_i}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \quad (5)$$

where n is the total number of years. x_i is the serial number of year i, e.g. the serial number of the year 1992 is 1, the serial number of the year 2010 is 19. C_i is the CO_2 emission amount in the ith year.

The temporal variation trends of China's CO_2 emissions were then classified into 5 types: slow growth, relatively slow growth, moderate growth, relatively rapid growth and the rapid growth. The classification criteria are presented in Table 2.

4. Results and discussions

4.1. Temporal and spatial variations of China's national city-level carbon emissions

4.1.1. Temporal variations of China's carbon emissions

The nationwide city-level CO_2 emissions of China from 1992 to 2010 are presented in Fig. 4. During the past 19 years, China's total CO_2 emissions had increased by approximately 6.78 times from 1.49×10^{10} t in 1992 to 1.01×10^{11} t in 2010, at an average annual growth rate of 11.22%. The CO_2 emission process could be divided into four periods: 1992–1999, 1999–2002, 2002–2007 and 2007–2010. During

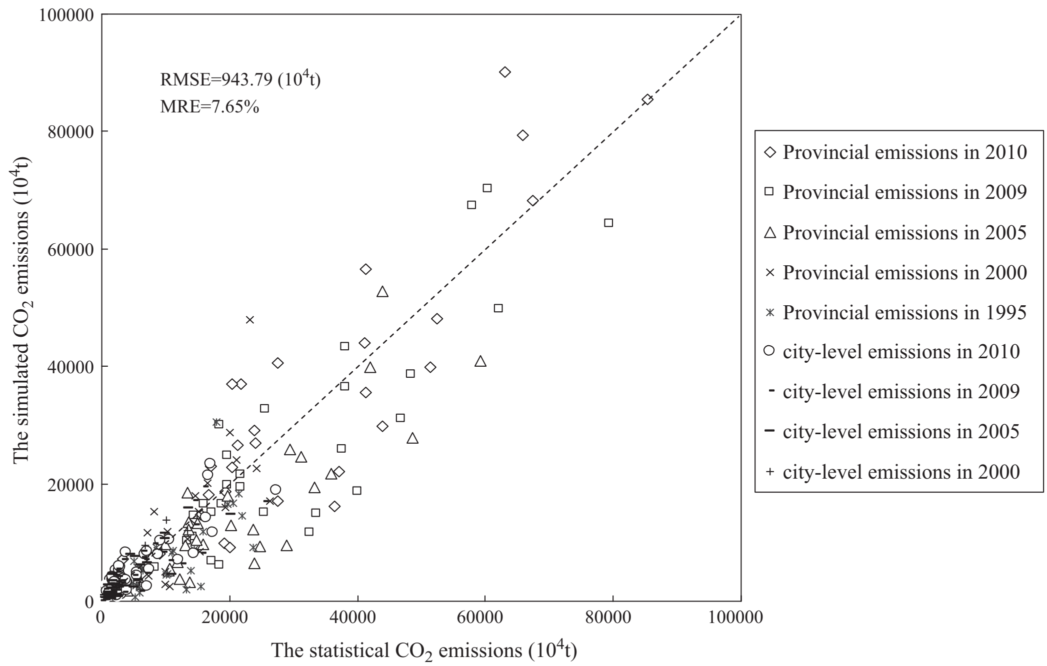

Fig. 3. Validation scatters between CO_2 emissions calculated from statistical energy consumption data and CO_2 emissions simulated from DMSP/OLS nighttime light imageries.

Table 2
Classification criteria of the temporal variation trends of China's CO_2 emissions using SLOPE indices.

Increase type	Slow growth	Relatively slow growth	Moderate growth	Relatively rapid growth	Rapid growth
SLOPE indices	$<\overline{C}-0.5s$	$\overline{C}-0.5s\sim\overline{C}+0.5s$	$\overline{C}+0.5s$–$\overline{C}+1.5s$	$\overline{C}+1.5s$–$\overline{C}+2.5$	$>\overline{C}+2.5s$

Note: $\overline{C}$is the mean amount of CO_2 emission and s is the standard deviation for Chinese Mainland from 1992 to 2010.

the period 1992–1999, the total nationwide CO_2 emissions increased gently, at an average annual growth rate of 7.59%. Following, there was a rapid increase from 1999 to 2002 at an average annual growth rate of 12.82%. The growth speed slowed down from 2002 to 2007. During the recent period 2007–2010, another rapid process took place again in China. The amount of CO_2 emissions increased approximately 4.23 billion during the last 4 years, nearly equaling to the total amounts of the previous 15 years. On the whole, China's 19-year CO_2 emissions process could be separated into two rapid periods (1999–2002 and 2007–2010) and two slow periods (1992–1999 and 2002–2007).

In order to quantify the temporal variation trends of China's city-level CO_2 emissions from 1992 to 2010, the SLOPE index method was used to classify the increasing trends of China's CO_2 emissions and corresponding classification criteria were introduced in Section. Results are shown in Fig. 5. There were 126 cities with slow growth rate and 168 cities with relatively slow growth rate, covering 28.33% and 48% of Chinese Mainland areas respectively. Meanwhile, there were 12 cities that belonged to the rapid growth type and 32 cities belonging to the relatively rapid growth type, covering 2.11% and 10.94% of Chinese Mainland areas respectively. Most cities in Western, Central and Northern China belonged to the slow growth type (except for Chengdu, Chengqing and Xinjiang), while most cities in Eastern China along the coastal lines belonged to the moderate and rapid growth types. The spatial variations of the growth rates of China's CO_2 emissions were mainly caused by the different economic development speeds between Western, Central, Northern and Eastern China.

4.1.2. Spatial variations of China's carbon emissions

The differences of CO_2 emission growth rates in four economic regions indirectly indicated that spatial clustering phenomenon of China's CO_2 emissions probably became increasingly obvious from 1992 to 2010. Therefore, the time-series global Moran's I indices were calculated to clarify the spatial cluster conditions of China's nationwide CO_2 emissions. Scatter plots of 300-city's global Moran's I indices in 1995, 2000, 2005 and 2010 are shown in Fig. 6. Results showed that there were significant positive spatial autocorrelations of CO_2 emissions from 1992 to 2010. In addition, the global Moran's I index increased from 0.3848 in 1995 to 0.4781 in 2010, which meant that China's CO_2 emissions became more and more clustered during the past 19 years.

Local Moran's I indices of each city in 2010 were further calculated to analyze the regional spatial clustering patterns of China's current CO_2 emissions between neighborhood cities. The cluster conditions of China's neighborhood cities were classified into four types (Fig. 7): High–High cluster, High–Low cluster, Low–High cluster and Low–Low cluster. The High–High cluster type meant the spatial agglomerations of neighborhood cities with huge amount of CO_2 emissions. Contrarily, the Low–Low cluster type meant the spatial agglomerations of neighborhood cities with small amount of CO_2 emissions. While the High–Low and Low–High types indicated there were great differences in CO_2 emissions between neighborhood cities. Result showed that the High–High cluster phenomenon was clearly identified in the coastal regions such as the Pearl River Delta, Yangtze River Delta, Shandong Peninsula and Jingjintang

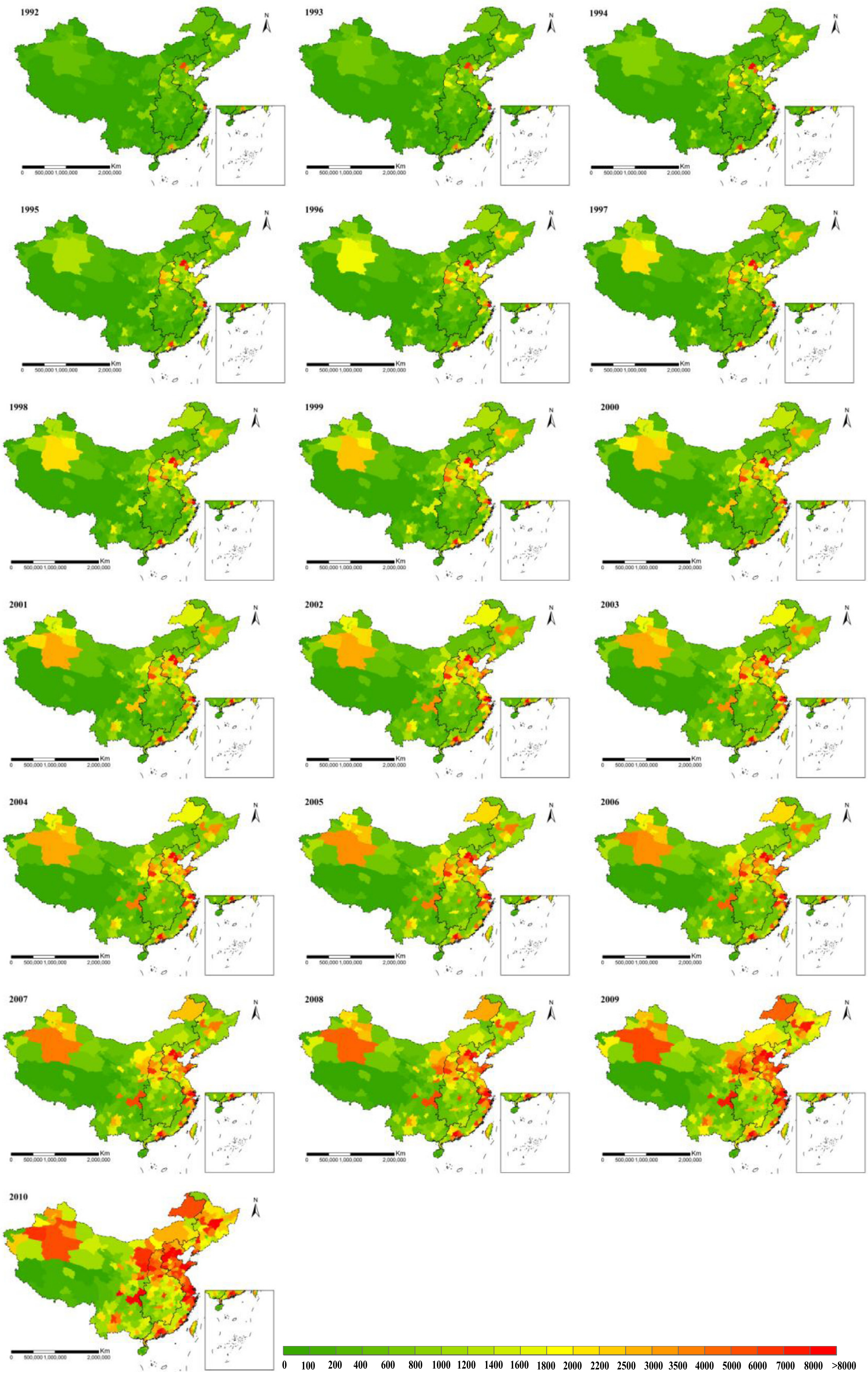

Fig. 4. Temporal variations of China's national city-level CO_2 emissions (unit: 10^4 t) from 1992 to 2010.

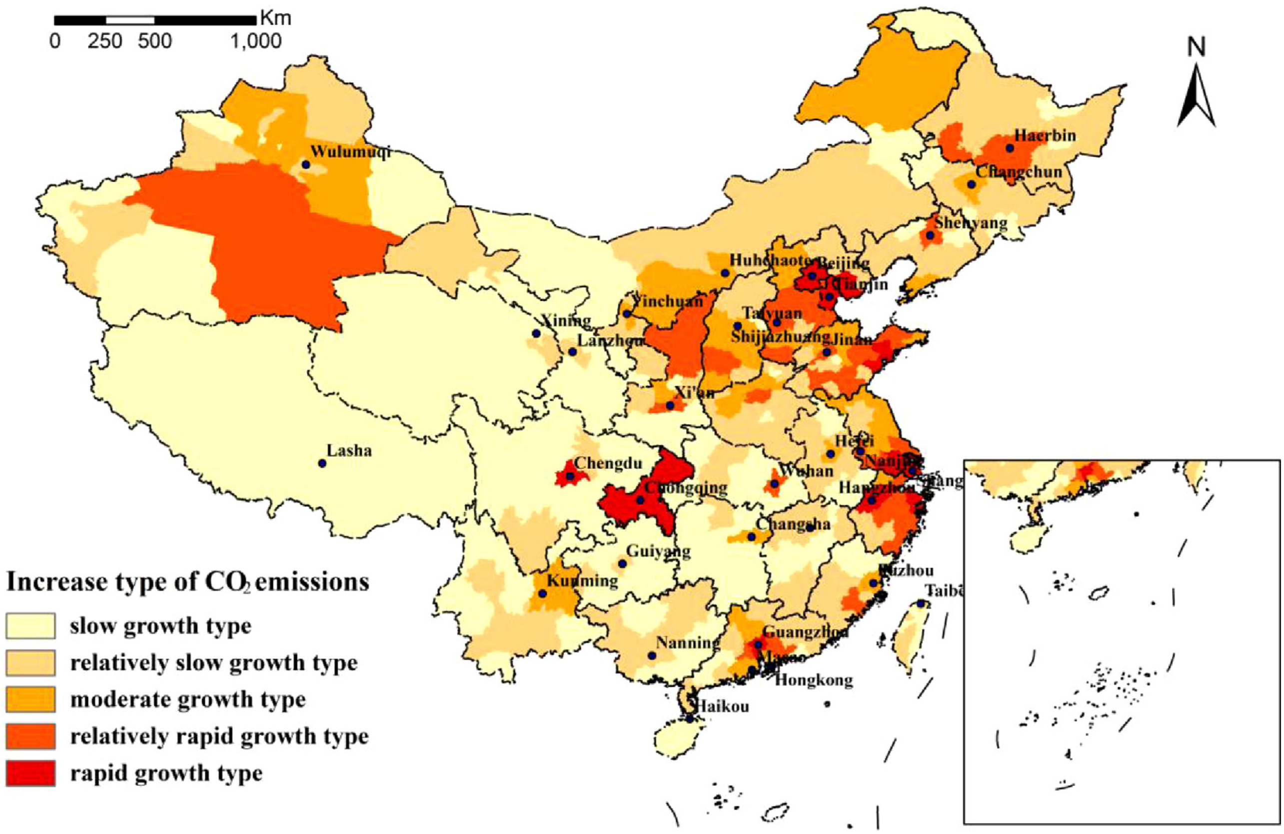

Fig. 5. Five classification types of the increment rates of China's national CO_2 emissions from 1992 to 2010.

regions around Beijing. While the Low–Low spatial clusters mainly were located at the western regions along the Tibet–Qinghai–Gansu provinces, Hubei–Hunan–Guizhou–Guangxi provinces, as well as Jiangxi and Hainan provinces (Fig. 7).

4.2. Comparison of the carbon emissions and carbon emission intensities between the four economic regions

4.2.1. Carbon emissions between the four economic regions

Consistent with China's nationwide temporal trends, the CO_2 emissions of 4 major economic regions also increased continuously during the past 19 years. However, there were great differences between the proportions accounting for China's total CO_2 emissions (Fig. 8). It was could be explained by the discrepancies in the regional economic development levels, policy guidelines and industrial structures between the 4 economic regions at different periods.

Eastern China was the largest CO_2 emission region in Mainland China. In general, it varied slightly during the whole time period, averagely sharing 52% of the nation's total amounts. In early 1990s, the proportion of eastern region was about 50%. After the 14th National Congress of Communist Party of China, China's economic reform and modernization entered into a new stage. As the "already gotten rich" region, Eastern China rapidly gathered a large number of human population and generated huge amounts of economic activities. The proportion of CO_2 emissions jumped to 54.28% in 1994. Following, a series of policies and measures were implemented to promote the economic developments of inland provinces and to balance the differences between coastal and inland regions. Consequently, the proportion of CO_2 emissions in Eastern region contiguously decreased slightly during years 1995–2007. Since 2008, Eastern China no longer simply focused on the rapid growth of GDP, but mainly on how to optimize the economic structures. During this period, the proportion of Eastern region dropped suddenly to 48%.

For Central China, the proportion of CO_2 emissions always fluctuated between 17% and 19% and showed stable trend from 1992 to 2010. It was mainly attributed to the stable growth rates of economic developments and unchanged economic policies in this region.

For Western China, the CO_2 emission proportions continuously increased year by year. In the early 1990s, the proportion was only about 15%. After implementing the Western Development Strategy of China, the CO_2 emission proportion of Western region instantly increased to 18.71% in 2000. However, the economic growth rate of Western China slowed down after the year 2000, due to lack of continuous fund investments and positive economic policies. The proportion of CO_2 emissions increased only 1.03% from 2000 to 2005. During the 11th Five-Year Plan period of China, the Western Development Strategy was again raised by the Chinese government, leading to another rapid economy development in Western region. From 2008 to 2010, the proportion of CO_2 emissions increased by nearly 1.65% per year.

For Northeastern China, the CO_2 emission proportions continuously decreased year by year since the 1990s, due to the economic falling of the Old Northeast Industrial Bases. Till the year 2008 when the Chinese government planned to re-develop the economy of the Old Northeast Industrial Bases, the Northeastern region underwent the fastest growth of GDP since the Reform and Opening Up period of China. The proportion of CO_2 emissions thereby jumped nearly 3% higher than the past year.

4.2.2. Carbon emission intensities between the four economic regions

Throughout the past 19 years, the CO_2 emissions per capita (PCCE) in all four major economic regions increased faster and faster

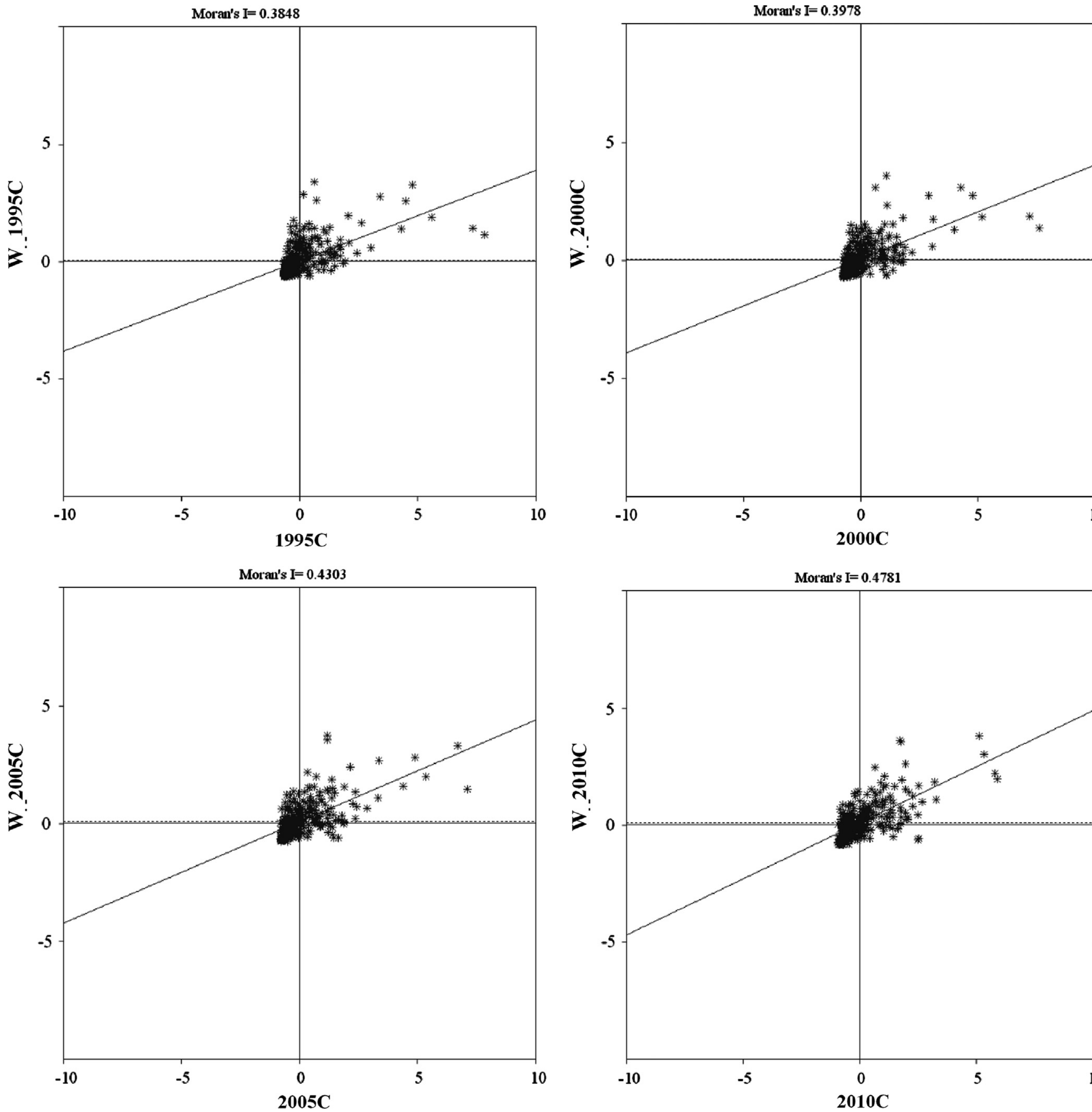

Fig. 6. Global Moran's *I* indices of China's national CO_2 emissions in 1995, 2000, 2005, and 2010.

year by year (Fig. 9), which was inconsistent with the continuous increments of regional GDP. Generally, the PCCE of four major economic regions basically maintained the following orders: Eastern China > Northeastern China > Western China > Central China. In Eastern China, the highest regional PCCE was mainly due to the huge energy consumptions by the large amounts of industries and great economic developments. Surprisingly, the second highest PCCE was found in Northeastern China. It was believed that the high PCCE of Northeastern China was mainly because of its industrial structures, most of which belonged to heavy industries. These heavy industries usually consumed large amounts of energy with low energy utilization efficiencies and therefore resulted in the second highest PCCE in China's four economic regions.

The CO_2 emissions per GDP (PGCE) of Northeastern and Western China were much higher than that of Eastern and Central China (Fig. 9). Because the industrial structures of Eastern and Central China mainly belonged to technology-intensive, labor-intensive and light industry type; the energy efficiencies were much higher than those of Northeastern and Western China, whose industries mainly belonged to heavy type and resource-intensive type. Therefore, it was believed that industrial structures, which determined the total energy consumptions and energy efficiencies, were the major influencing factors of PGCE.

PGCE of four major economic regions decreased gradually from 1992 to 2008. During the China's national 10th Five-year Plan period (2000–2005), the Chinese government vigorously advocated energy saving and emission reduction. Most energy-related companies, therefore, were forced to bring in new technologies to improve energy efficiencies, leading to continuous growth of regional energy efficiencies during the years 2002–2008. Thereby, the PGCE of all

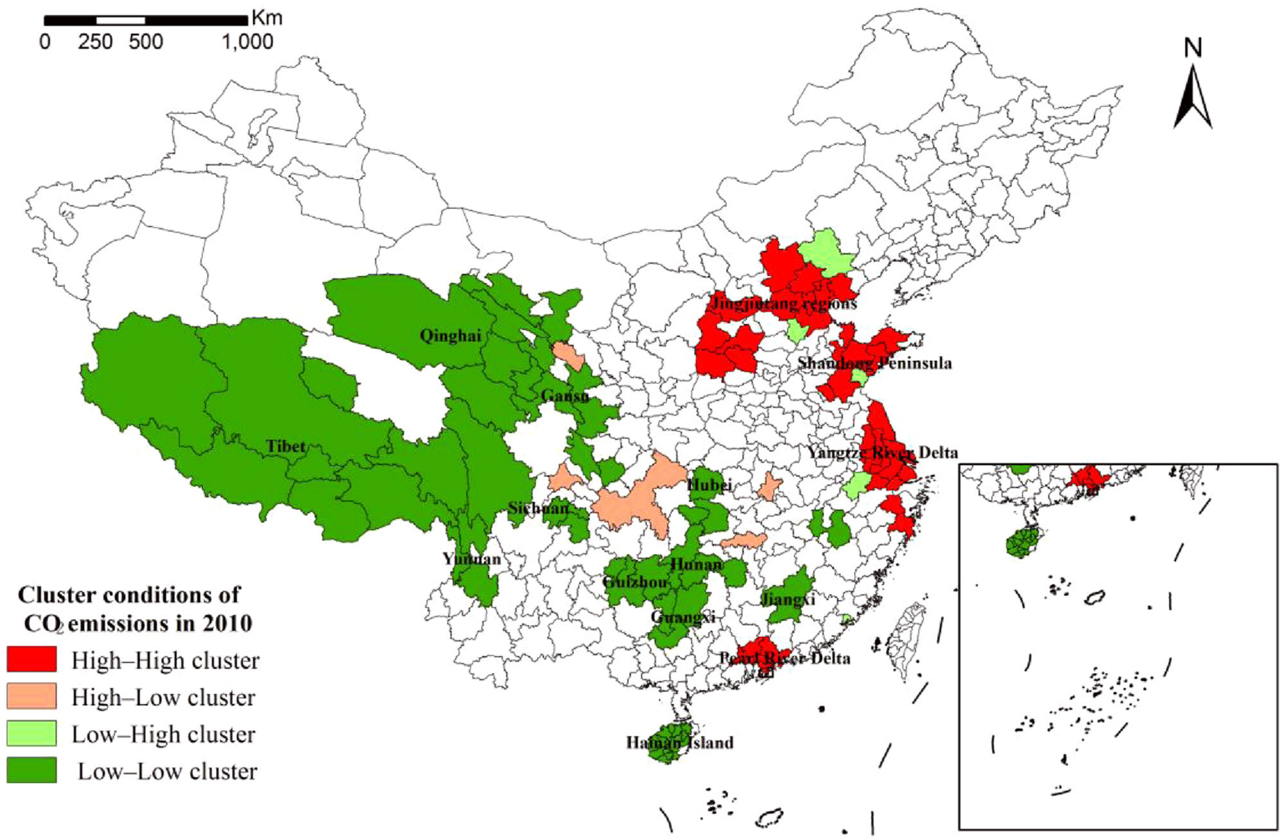

Fig. 7. China's CO_2 emission cluster conditions of neighborhood cities in 2010.

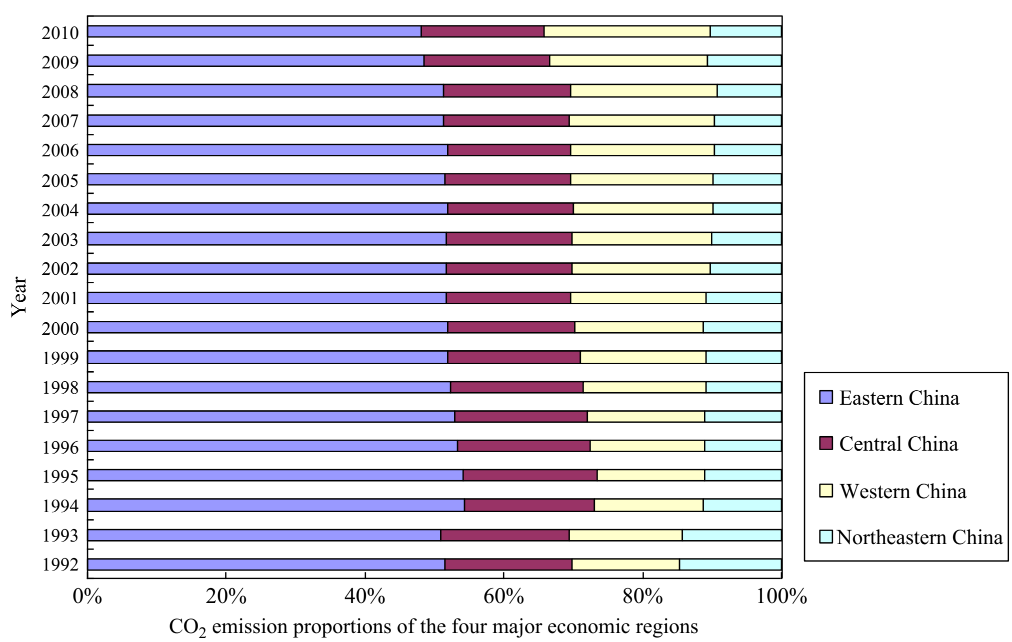

Fig. 8. Proportions of the 4 major economic regions accounting for China's total CO_2 emissions from 1992 to 2010.

four major economic regions decreased significantly from 1992 to 2008. However, the temporal trends of PGCE in Northeastern and Western China turned to increase suddenly at an average annual growth rate of 12.5–13% since 2008. This trend matched well with the time point that the Chinese government implemented the economic policies of vigorously developing heavy industries and energy industries in Northeastern and Western China, which thereby resulted in the obvious growths of regional PGCE.

4.2.3. Different carbon emission characteristics between certain representative cities and provinces

In order to further study the carbon emission characteristics for making regionalized mitigation suggestions, the double mass curves of cumulative energy consumptions against cumulative CO_2 emissions of 10 representative cities or provinces (Beijing, Tianjin, Guangdong, Shanghai, Henan, Hubei, Heilongjiang, Liaoning, Shanxi and Yunnan) were produced (Fig. 10). The slope of the

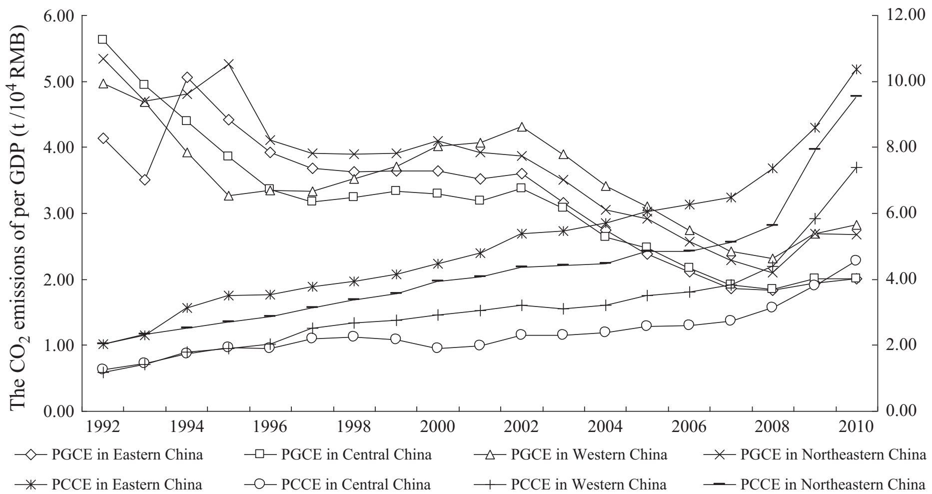

Fig. 9. PCCE and PGCE of the four major economic regions from 1992 to 2010.

double mass curve actually presented the mount of CO_2 emission changes along with the energy consumption changes per unit, which meant the variations of CO_2 emissions per energy consumption (PECE).

Results could clearly reveal the different variation characteristics of PECE between these representative cities and provinces. The PECE of Beijing and Tianjin cities changed little during these years, which were mainly due to the stable economic developments and corresponding policies of Beijing–Tianjing–Tangshan economic zone around China's capital. As for Guangdong province and Shanghai city, which were representatives of the Southern and Eastern coastal economic zones respectively, the PECE decreased obviously at 2005–2006 periods due to the optimizations of its economic structures. However, the PECE of Central (Henan and Hubei provinces), Northern (Heilongjiang and Liaoning provinces) and Western (Shanxi and Yunnan provinces) regions all increased significantly since the 2009–2010 periods due to their regional economic developments. It was separately because Central regions mainly received the high-carbon-emission industries that were forced out by the Eastern regions, Northern regions mainly developed the heavy-industries that consumed huge energies, while most industries in Western regions were immediate energy intensive ones.

4.3. *Potential driving forces and mitigation policies*

4.3.1. *Driving forces*

Our results revealed that the characteristics of CO_2 emissions varied greatly among the four economic regions. Most cities in Western and Northern China belonged to the slow growth type, while most cities in Eastern and Central China along the coast belonged to the rapid growth type. These variations were mainly caused by the different economic developments between Eastern, Central China and Western, Northern China. In other words, the amounts of CO_2 emissions were mainly determined by the regional total GDP, while the growth rates of CO_2 emissions were mainly determined by the GDP increments.

For the CO_2 emission intensities in the four economic regions, PCCE of Northeastern and Eastern China were higher than those of Western and Central China. Meanwhile, PGCE of Northeastern and Western China were higher than those of Eastern and Central China. Results indicated that the spatial and temporal patterns of CO_2 emission intensities were mainly determined by the regional industry types and energy efficiencies. Because light industries and high-tech companies consumed less energy with higher energy efficiencies, so the PCCE and PGCE of Eastern and Central China, which were mainly located by technology-intensive, labor-intensive and light industry types, were relatively lower. Contrarily, the energy-related and heavy industries were mainly distributed in Northeastern and Western China. As energy-related and heavy industries were more likely to consume more energy with lower energy efficiencies, therefore the PCCE and PGCE of Northeastern and Western China were relatively higher. Industry structures and energy efficiencies were therefore two important factors determining the differentiations of China's regional CO_2 emission intensities.

In summary, GDP was the determining factor affecting the national total CO_2 emissions of China. Industry structures and energy efficiencies were two important factors determining the CO_2 emission intensities.

4.3.2. *Regionalized mitigation guidelines*

In order to decrease the total amount of China's CO_2 emissions but not hinder the growth rate of national GDP, the major efforts should be focused on optimizing the industrial structures and guiding companies to improve the energy efficiencies. Specific strategies were suggested as follows.

As the industries of Western and Northeastern China were mainly energy-related and heavy industries, more attention should be paid to the optimizations of regional energy structures and improvements of energy efficiencies in these regions. However, because Western and Northeastern China were being at an early stage of economic developments, it was impossible to completely alter the single-factor-dominated (coal-dominated) energy structures in a short term. It was probably more effective and feasible in a short period to reduce carbon emissions by improving the energy efficiencies of energy transformation, utilization and recycling processes. Besides, most Western and Northeastern regions were located in high-altitude or high-latitude areas, where abundant solar and wind energy resources existed. Therefore, in a long run, these regions should gradually exploit such renewable energy resources and develop diversified-energy-dominated structures to replace the coal-dominated structure.

For Eastern and Central China, the industries mainly belonged to technology-intensive, labor-intensive and light industry types. Because the Eastern and Central regions were already at a relatively high development stage of economic developments, industry structure optimization was also an urgent task of economic development for these regions at present. So the recent mitigation strategies of CO_2 emissions should focus on the industry structure adjustments and optimizations. High-tech manufacturing, financial, service and internet industries with low carbon emissions should be vigorously supported. High energy-consumed industries such as the chemical, metal and power-related ones

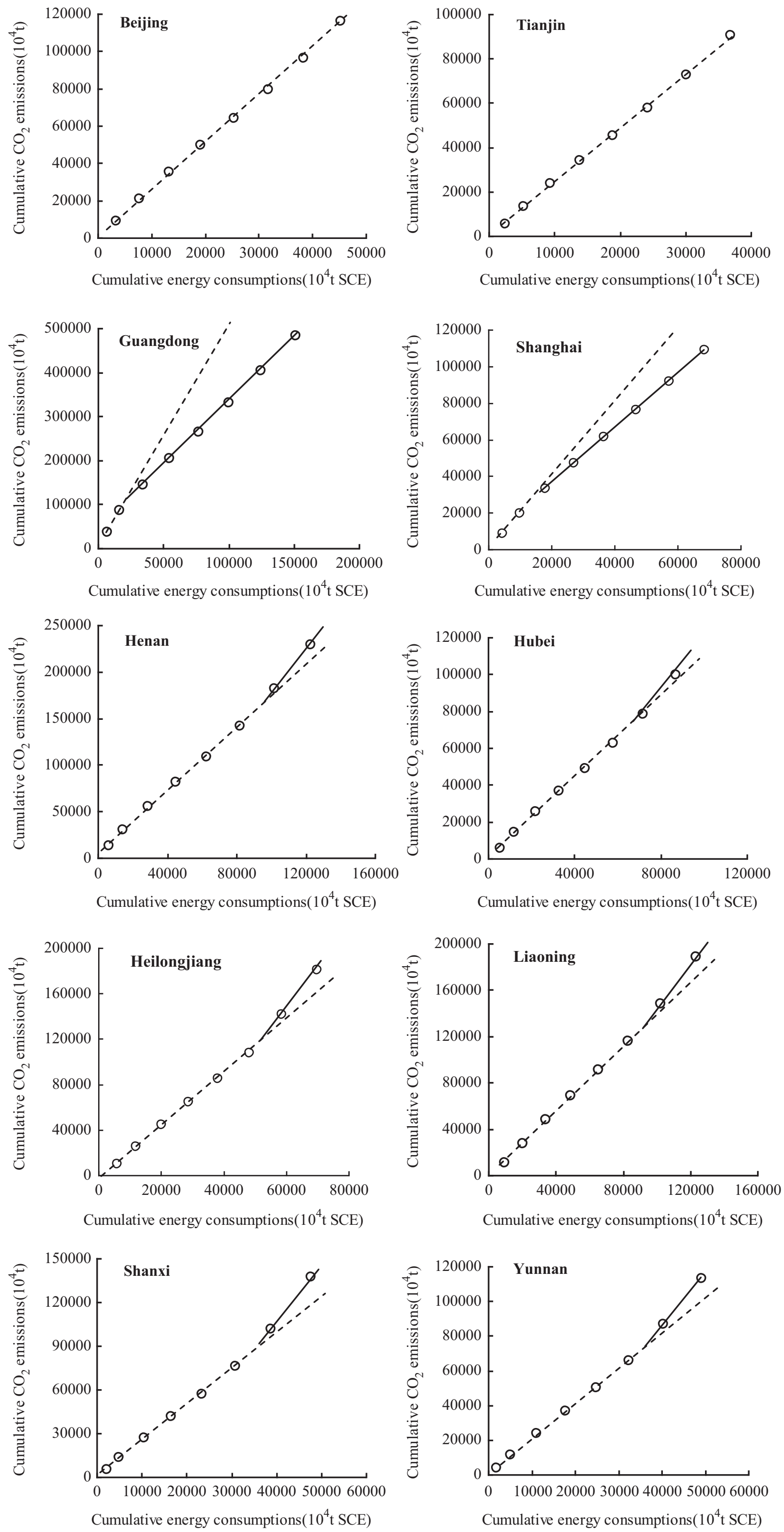

Fig. 10. Double mass curve between cumulative energy consumptions (10^4SCE) and cumulative CO_2 emissions (10^4 t).

should be shut down or reformed by improving the production technologies, processes and equipments.

Corresponding polices and laws should be made in time to benefit the mitigation goals. In Western and Northeastern China, tax and loan preferences and financial subsidies could be given to companies which developed advanced technology with low carbon emissions or used renewable energy. Meanwhile, extra taxations should be laid on energy-related industries in Eastern and Central China.

Additionally, according to the different carbon-emission characteristics between 10 representative cities and provinces, the PECE in high-developed Southern and Eastern coastal regions were in the trend of declining. However, PECE in developing and undeveloped regions has started to increase significantly. So, Chinese government

should not mainly focus on reducing the CO_2 emission intensities of the high-developed cities or provinces. Contrarily, much more efforts should also be made to prevent the CO_2 emission intensities of underdeveloped cities or provinces from increasing rapidly at the early stage of economic developments.

5. Conclusions

The total CO_2 emissions of China increased from 1.49×10^{10} t in 1992 to 1.01×10^{11} t in 2010, with average growth rate equaling to 11.22%. Most cities in Western, Central and Northern China belonged to the slow growth type, while most cities in Eastern and Southern China belonged to the moderate and rapid growth type. GDP increment was the major factor determining the growth rate of total CO_2 emissions. Cities with huge amounts of CO_2 emissions mainly agglomerated in the southern and eastern coastal areas, while spatial clusters of cities with small amounts of CO_2 emissions mainly appeared in southwestern inland areas. PCCE of Northeastern and Eastern China were higher than those of Western and Central China. Meanwhile, PGCE of Northeastern and Western China were higher than those of Eastern and Central China. Industry structures and energy efficiencies were two important factors influencing the intensities of regional CO_2 emissions.

Considering the spatial and temporal patterns of CO_2 emissions between the four economic regions, the mitigation strategies for Eastern and Central China should mainly focus on the industry structure adjustments, while Western and Northern China should pay more attention to the optimizations of regional energy structures and improvements of energy efficiencies.

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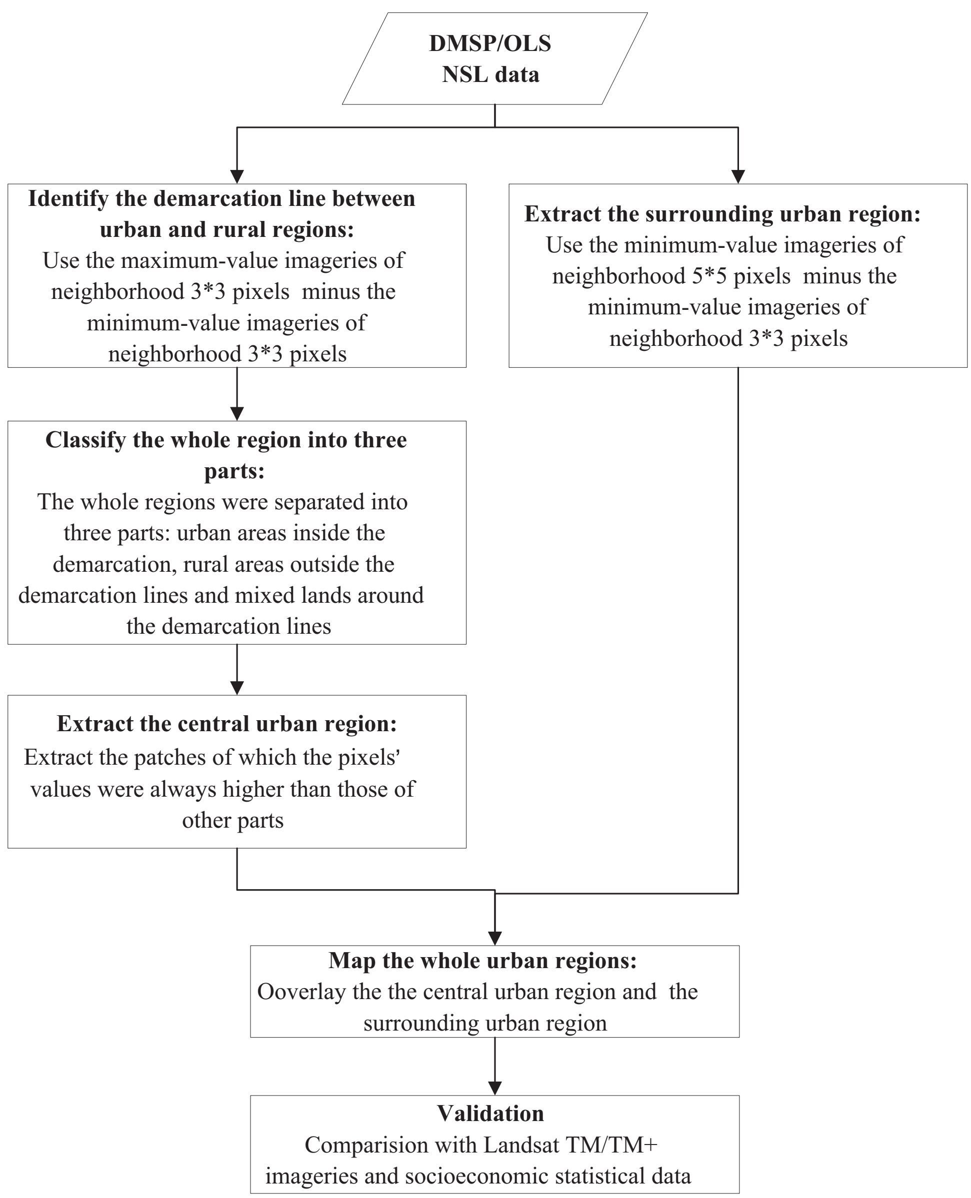

Fig. A1. Technical route for extracting urban regions using DMSP/OLS nighttime light imageries.

Appendix A

In the DMSP/OLS imageries, there were obvious “peak” and “valley” regions, which were called the “light” and “dark” centers respectively. Among the “light” centers and “dark” centers, there were always some places, where the night lights suddenly changed. These places were the transitional boundaries between urban and rural regions. This paper developed a unique urban lands extraction method on basis of the above characteristics of DMSP/OLS imageries (Fig. A1). The demarcation lines between urban and rural places were firstly indentified by deriving the topographic imageries using the maximum-value imageries of 3×3 pixels to minus the minimum-value imageries of 3×3 pixels. The whole regions were then separated into three parts: urban areas inside the demarcation lines, rural areas outside the demarcation lines and mixed lands around the demarcation lines. As the pixels' values of urban places were always higher than those of rural places, we could immediately distinguish the central urban areas out of the three parts.

Generally, the pixel values near light centers and dark centers both varied slightly, while the pixel values near the demarcation lines decreased quickly from urban lands to rural lands. Hence, the minimum-neighborhood imageries generated from original NSL imageries differed significantly near the demarcation lines, but much similar near both light centers and dark centers. This paper derived two minimum-neighborhood imageries from DMSP/OLS NSL data by generating the minimum values of neighborhood 5×5 pixels and 3×3 pixels. The surroundings urban regions could be easily distinguished by minusing the imageries of neighborhood minimum values based on 3×3 pixels from the imageries based on 5×5 pixels. Using this method, the surroundings urban regions hidden at the demarcation lines could be easily extracted. Finally, the whole urban places could be obtained by overlaying the central urban regions and surrounding urban regions. The construction lands extracted from DMSP/OLS NTL imageries agreed well with those mapped from TM/ETM+ imageries (OA=0.953, Kappa=0.91).

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